Chapter

Adapting Disruptive Applications in Managing Quality Control Systems in Intelligence Manufacturing

Amusan Lekan, Clinton Aigbavboa, Moses Emetere and James Owolabi

Abstract

Controlling quality has become a major trend in the circle of manufacturers and production managers that engage in intelligent manufacturing all over the world, on account of industry 4.0, in recent times. Intelligent manufacturing therefore is the use of advanced applications, analytics, sensors and Internet of Things (IoT) to improve manufacturing. The aim of the study is to carry out a study on application of disruptive application in managing quality system in intelligent manufacturing with a view to improving manufacturing process in organizations. Survey methods was used in collating responses from production managers of manufacturing companies at selected locations censoring production managers and supervisors on some parameters such as areas of disruptions in the quality assurance monitoring and calibration in production process, issues and challenges involved in quality control systems in manufacturing, Man-Whitney U Test, T-test, Pearson's Test were used to analyze the collated data. Also, this study presents advanced analytical tools and applications to improve quality in manufacturing process. The study finally presents areas of disruptions in the quality assurance monitoring and calibration in production process, issues and challenges involved in quality control systems in manufacturing, emerging areas of application and recommendation for improvement.

Keywords: quality, system, intelligence, adaptation, disruption, manufacturing, process

1. Introduction

Quality control issue is one of the cardinal factors in product manufacturing. It entails profiling areas where quality is to be maintained and enforced. In manufacturing parlance, quality could be described as process and protocol of the needful to ensure that the product is maintained at highest peak value. However, quality has been a watch factor that has resulted in industrial productivity birthed by technological innovation. [1] submitted that defining quality from different perspectives depends on the individual philosophical point of view. Whichever perspective adopted among several perspectives available, the authentic definition is the one that was premised around definition of American Society of Quality. American Society of Quality defines quality as an embodiment of totality of manufacturing essence which is positioned to satisfy an implied need or consumers' product need and expectation [1]. Also, [2] viewed quality as an identity of production essence while [3] described quality as collection of different hall-mark of production optimizations, expressed in implementable units. Therefore, it worth a while controlling the process that lead to formulation of quality, then controlling cost at different stage of production would be very easy. The important nature of quality control in industrial manufacturing therefore necessitates the establishment of control system during industrial production process.

Quality control system according to [3, 4] ensures emergence of quality product as output of manufacturing process. Quality control system enables the engagement of different techniques and process to ensure quality production output. Some of the techniques according to [4–6] has yielded tremendous results in the past and still remain relevant in the scope of industrial production and manufacturing till date.

However, some of the techniques and tools are gradually becoming obsolete and yielding reduced performance in term of output, therefore there is a need for gradual replacement of old methods with automation techniques, in order to sustain the tempo of productivity. This fact necessitate research in the area of quality assurance in industrial manufacturing. Adventure for development of new quality assurance system and methods of production that is automation based lead to evolution of Industry 4.0, which has since then changed the industrial manufacturing game [6]. Introduction of industry 4.0 with artificial intelligence into the manufacturing system has brought about replacement of old mechanical based method with new and smarter machine technique with automated system that uses sensors, this according to expert has changed procedures often used in quality checks in manufacturing sector. However, artificial intelligence has brought up application of robotics in industrial application and also the use of applications that has been empowered with sensors for automation capability. Smarter machine according to [5, 7] has led to enhanced productivity, improved quality standard and products.

Finally, in [5, 8] it was alluded that innovation of smarter machines, sensor enable machine has been a major addition from industry 4.0 technological disruption, that brought about intelligent manufacturing, it is on this premise that this study investigated system and process of adapting disruption technology in quality control monitoring to be able to achieve results oriented intelligent manufacturing.

1.1 Aim and objectives

1.2 Aim

The aim of the study is to carry out a study on application of disruptive application in managing quality system in intelligent manufacturing with a view to improving manufacturing process in organizations.

1.3 Objectives

There is a need to articulate objectives of the study, the objectives were synthesis from the gaps and emerging thoughts from literatures consulted. Therefore the following objectives are used in this study. They are to:

i. Investigate the state of disruption in quality monitoring in industrial manufacturing

ii. Examine the Drivers of Effective Quality Control System Monitoring in Intelligent Manufacturing

iii. Study Issues and Challenges Involved In Quality Control Systems in Intelligent Manufacturing

iv. Profile Critical Factors Influencing Adaptation of Effective Intelligent Manufacturing Process.

2. Literature review

In this section review of concept was carried out, and constructs were gleaned from the objectives and the aim and the title of this study. Therefore the review covers the following area: quality control, areas of disruption in quality monitoring and intelligent manufacturing. It includes the following: intelligent manufacturing system, quality control in manufacturing industry, industry 4.0 application disruption in quality assurance monitoring and challenges in quality control system.

2.1 Intelligent manufacturing system

The world of manufacturing environment has changed drastically in recent times, on account of industrialization. Also paradigm in production process, design and implementation has shifted in the direction of application of new generation applications, the applications could be found in design, monitoring and marketing industries. The new application has capability to accommodate high volume product processing, complex system and flexible schedule and sequence. The new system is referred to as intelligent system. The word intelligence comes from the new packages that comes with electronic tools that are now in popular use in industrial manufacturing [9]. The authors described intelligent system as electronic and automation replacement of traditional mechanical functions with new applications that uses sensors and sensitive Nano-tubes applications. In another clime, it is referred to as automatic system which found integration in design and monitoring system as pointed out in [9, 10].

Intelligent system is highly used in monitoring process during industrial manufacturing of products. Intelligent production systems are operated as a calibrated design and monitoring system, they are used in sequential monitoring of production system. They are used to monitor highly complex manufacturing system in order to achieve flexible manufacturing for instance, [10–12] submitted that intelligent system has enabled the use of sensor, optimization parameters, laser beam application and laser beam machine process. This according to [10] described the introduction of intelligent manufacturing system as a step ahead of traditional manufacturing system. The claim lies in the fact that intelligent manufacturing has capability of self-analyzing, self-learning, complexity apprehensions and large data storage. The self -analyzing attribute of systems of intelligent component is rooted in attribute of intelligent application that consist of the use of sensors. The sensors are mounted on tools and machine for quality control attribute in areas such as sequencing, intelligent scheduling, intelligent control and maintenance.

Moreover, in intelligent manufacturing, scheduling and sequencing are “sin-qua-non” there is interrelationship between the two concepts. The concepts tend to reoccurs throughout the production process because of its high utility. Also, [13] posited that intelligent algorithm was designed to assist in parametric calibration of some intelligent applications used in manufacturing industries. Algorithms are used in Asia and European industrial manufacturing sectors in permutation control of scheduling and sequencing operation. Scheduling operations involved scheduling of machine operations, allocation of resources of money, man, human and machine among others. [12, 14] in scheduling operations, parameters setting is of utmost importance. Some of the parameters was discovered by Johnson in 1965, scheduling was classified by Johnson into two categories; the flow shop and job shop. In concurrent intelligent scheduling, the flow shop utilizes Toyota production system in a way that the system could accommodate large volume of work per time, this view was supported in [14–17].

The choice of scheduling technique often depends on complexity, desired output and volume of system at hand. There are two conditions under which scheduling could be applied, the flow shop and job shop. Flow Shop in manufacturing and production process refers to high volume system that uses highly standardized equipment to ensure continuous flow of standardized products e.g. refineries, cement company, drinks production. Similarly, Job Shop is a low volume system, which periodically shift from one job to another. The production is often according to consumers' specification and orders are in small units [16, 17]. Moreover, sequencing is about methodical approach to processing loading jobs at work station. It describes the order in which jobs are processed or should be processed at work centers. In traditional scheduling operation the following rules subsists; the widely acceptable rules for scheduling operation in intelligent manufacturing according to [16–18] includes the following: First come First Serve (FCFS): Processing job in the order of arrivals at work center. Shortest Processing Time (SPT): Job are processed based base on length of processing time and Earliest Due Date (EDD): This rule sequences jobs according to their due date. Shortest due date are processed.

2.2 Quality control in manufacturing industry

In manufacturing sectors there have been gaps in the users request for product and the quantity of product manufactured to meet the requests, this trend, tend to permit packaging low quality products into markets. However, high level of quality is demanded as part of users demand expectation. In contemporary times, users expect faultless product, which has put more pressure on the manufacturer and their production outfits. Therefore, there should be shift from traditional ways of enforcing quality so as to enhance manufacturing productivity. Manufacturers' bid to improve quality has led cutting edge researches in quality control process, this therefore lead to new realm where quality control methods and processes are digitalized and this concept is termed quality 4.0. Quality 4.0 borders about the use of enhanced system to collect information about the design, behavior, use and performance of products in market. The quality 4.0 involve the use of benefits of Artificial intelligence (AI). Artificial intelligence works according to [19] through identifying faults in product with AI algorithm, the AI algorithm having been calibrated in fault identification would notify quality team of emerging faulty product. Similarly, quality control charts are often used alongside with AI in quality monitoring and also through pictorial illustration of quality trend in production batch, for instance in [20] simple statistical analysis method was used in interpreting quality results. It was noted in [21], that Japan adopted statistical method and tools in quality management. In Japan, certain quality control system has been in use in the manufacturing sector, for instance [20] submitted that the following system has been consistently engaged in intelligent manufacturing quality control in Japanese production process; Ishikawa, flow chart, figure and diagrams, pareto analysis, checklist and correlation among others. [21] identified six sigma template as being a useful tools as well in quality control monitoring process. Similarly, product reliability is also another measure introduced in ensuring quality in product development [22] presented quality control methods that could be used to enhanced productivity and safety [23]. Worked on systematic ways of presenting reliability analysis of control system, that, it has tendency of improving product reliability, strategies and implementation. System and reliability analysis is for the purpose of quality control during product design and manufacturing and control stage. The system was described in [22] as consist of mathematical model that can be used to describe relationship between product quality and control method. Product reliability process design include process conception, identification of product manufacturing process and robust design [22, 23].

2.3 Industry 4.0 application disruption in quality assurance monitoring

Industrial application in product manufacturing has introduced dimension of automation at various aspect of manufacturing. Generation of traditional manufacturing has metamorphosized into conventional system, thus, the new generation of industrial application covered different systems of conventional technology. In [24], systems that could enable product supply system to be optimized using key technologies such as cyber system, IoT (Internet of things), data analytics, big data, and expanded database. The key production points could be interlinked and interconnected or networked for effectiveness. Industry 4.0 enables digital interconnectivity among machine and work stations of production system. Similarly, industry 4.0 facilitates the interoperability of man and machine interconnected with digital guides [25]. However, industry 4.0 has different adaptability in different continent both in literary presentations and industrial application. In Japan, industry 4.0 is embellished as “New strategy”, China captured it as Made-in-Chine 2025 as contained in {48} while United states according to [24] referred to industry 4.0 as “reindustrialization”.

Industry 4.0 involved is centered on industrial reformation or reindustrialization and information applications contained in [26], this fact was corroborated by [27], which makes availability of quality supervisors and production managers. In nutshell, the component of industry 4.0 application in the portfolio of industrial manufacturing and production according as an inclusive component as viewed by [25, 28–30] and it consist of the following aspects in industrial production: IoT applications, learning factories, internet services, cloud computing and storage, cybernetics, cognitive computing, Artificial intelligence, robotics, data analytics, mechatronics, big data application, and sensor management among others.

2.4 Challenges in quality control system research (quality control implementation in

Right from the ancient days of product manufacturing, industrial application has experienced a lot of changes ranging from design parameters configuration of product design implementation. Companies and design expert has labor extensively to come up with perfect system, but there has always been one challenge or the other. Quality control system in intelligent manufacturing gas come with challenges. [31] Deloitte (2014) opined that, there are challenges associated with industry 4.0 digitalization and digital transformation.

Challenge of making reliable forecast is one of the major challenges often encounter in quality control management, however, [32] opined that the use of cyber technology equipment, physical system, artificial intelligence, big data would increase efficiency of running production system. Similarly, ineffective flow of materials and adequate planning has always been the bane of effective production system. [33, 34] argued that effective monitoring of flow system may not impart much on the production effectiveness unless match up with flow stream mapping.

Moreover, managing logistic tasks with material handling machine was suggested by [33, 35] that there is negative consequence that could come up on account of in appropriate adoption of material handling machine. Some of the consequences include absence: absence of route temperature, fluctuating environmental temperature, half-life of machine parts, and inadequate level of machine parts' management.

Furthermore, inadequate manpower planning, inadequate system calibration and continuous data transfer are some of the challenges that should be surmounted for effective quality control system during intelligent manufacturing [22, 36]. Finally, major challenge with the use of Artificial intelligence (AI) in creating intelligent manufacturing in recent time is the one that influence negatively, the variable of decision making and data inter- operability. [32] described parameters that influences AI adoption in control system to include: data parsimony, data transfer, data processing and manipulation, process speed, system efficiency and interoperability. Similarly, high data affinity or fidelity expectation, smart storage capacity and smart maintenance are components of smart and intelligent manufacturing that should be managed.

3. Materials and methods

In the context of this study, primary data was engaged and was collected from sampled Production managers, Production supervisors, Quality control officers and Information communication officers that are on ground at the selected locations of the research while Survey materials adopted structured questionnaire design in a closed structure manner as carried out in similar previous studies such as [13, 14, 16].

3.1 Material and tools

In this study different materials and tools were used, part of the materials used are A-4 papers for questionnaire production, Google forms, Google spread sheet, markers, pencils and biro. Analytical package of Statistical tools of SPSS was engaged in the processing of data collated from the respondents. Some of the tools include Relative Agreement Index (RAI), Mann–Whitney U-Test, Pearsons's Chi-square test and Student's T-test.

The Relative Agreement Index was calculated using the following relation.

$$\mathrm{RAI} = \sum \underline{\mathrm{Wi}} \qquad (1)$$

$$\mathrm{A} \times \mathrm{N}$$

where RAI = Relative Agreement Index, Wi = Weighted Sum, A = The number of items on Likert scale of 1–5.

N = individual weight of the scale item on Likert scale 1–5. The component of the Likert Scale include (SA: Strongly Agree (5), A: Agree (4); SD: Strongly Dis-agree (2); D:Dis-agree (1); N:Neutral (3)).

Survey design method was used in the study with population comprised of 100 manufacturing company both small and large scale. Similarly, sectionalized category of client were profiled and censored for data collection purpose, they include: Production Manager-PM; Quality Control Officer-QCO, Production Supervisor-PS; ICT Officer-Information Communication Technology Officer, the category of respondents were used in the study, they include the managers, officers and supervisors engaged in companies that are involved in consumer good products manufacturing, located at the at Federal Capital Territory in Abuja and Lagos state Nigeria. The questionnaires were initially pretested on five (5) respondents for content validation, their observation were later used to recalibrate the questionnaire into final form used for the analysis the view was supported in [13–15].

Summarily, the unique group of sample used in the study include sample size of seventy three (73) respondents that cut across the cadre of managers and supervisors in product manufacturing companies, i.e. Production Manager-PM; Quality Control Officer-QCO, Production Supervisor-PS; ICT Officer-Information Communication Technology Officer.

3.2 Questionnaire design

The data collection instrument adopted is a structured questions designed in Likert scale format of semantic rating scale 1–5. The questionnaire was designed in a way that allow for easy collation of data. It was divided into five sections. Section 1 was centered on the Bio-data information of the respondents, Section 2 was about categories of production manager, Section 3 was on Investigating the state of disruption in quality monitoring in industrial manufacturing, Section 4 was about the drivers of effective quality control system monitoring in intelligent manufacturing. Section 5 was centred on issues and challenges involved in quality control systems in Intelligent manufacturing while Section 6 focused on critical factors that influences an effective intelligent manufacturing system.

3.3 Operationalization of research variables

Question, analytical method	Scale	Variables	Reference
Q1–5 Respondents Bio-data information, Work experience. Analytical Methods: Descriptive Statistics, Percentage. Spearman Ranking.	Ordinal, Numeric, Likert Scale	Professional cadre, Gender, Types of managers, Qualification and cadre of managers on intelligent manufacturing system	[21]
Q6–14 Investigate the state of disruption in quality monitoring in industrial manufacturing Effectiveness of control systems Satisfaction level. Analytical method: Pearson's Chi-square, Kendal Tau teat and Relative Agreement Index and Spearman Ranking	Numeric Likert scale	Perception on state of adoption of quality control system for intelligent manufacturing	[20, 23]
Q15–23 Examine the Drivers of Effective Quality Control System Monitoring in Intelligent Manufacturing Analytical Method: Pearson's Chi-square, Relative Importance Index, Cronbach Alpha test, Man-Whitney U Test.	Numeric Likert scale	Drivers of Effective Quality Control System Monitoring in Intelligent Manufacturing system.	[21]
Q24–32 Study Issues and Challenges Involved In Quality Control Systems in Intelligent Manufacturing Analytical Methods: Pearson's Chi-square, Relative	Numeric Likert scale	Issues and Challenges Involved In Quality Control Systems in Intelligent Manufacturing	[20, 21]

Question, analytical method	Scale	Variables	Reference
Importance Index, Cronbach Alpha test, Man-Whitney U Test.			
Q33–42 Profile Critical Factors Influencing Effective Intelligent Manufacturing Analytical methods: Pearson's Chi-square, Kendal Tau teat and Relative Satisfaction Index and Spearman Ranking.	Numeric Likert Scale	Censoring satisfaction level on Critical Factors Influencing Effective Intelligent Manufacturing system	[20, 24]
Q43–51 Adaptable Areas of Disruptions in Quality Assurance Monitoring for Intelligent Manufacturing Analytical method: Relative Effectiveness Index, Kendal Tau Test. Spearman Ranking.	Numeric Likert Scale	Adaptable Areas of Disruptions in Quality Assurance Monitoring for Intelligent Manufacturing	[20]

3.4 Processing and distribution of questionnaire

In processing and administration of the data collection, survey design method was used while purposive sampling technique was adopted to pull together the respondents, as mentioned earlier in Section 2.2, the respondents used for this study are the production personnel, a total of eighty (80) questionnaire designed in Likert scale was sent to one eighty(80) managers and supervisors and officers that constitute respondents among which the completed and valid seventy three (73) questionnaire were used, this is similar to method adopted in studies of [13–15].

4. Results and discussion

4.1 Category of respondents

In the context of this study, different category of respondents were engaged in the study (**Table 1**). Twenty three (23) production supervisor are engaged, twenty (20) production managers, twenty (20) quality control officer and ten (10) ICT officers. All respondents are directly involved in production process of their various company at the research location.

4.2 Qualification of respondents

Manufacturing education background matters in the context of this research, level of enlighten would enable a respondent to contribute adequately towards valid response to the administered questionnaire or interview, Therefore, respondents qualification in this study is as presented in **Table 2**. It is obvious that the managers, supervisors and officers has more than one qualification. Among the 20 production managers sampled, 10 possessed trade certificates, 5 possessed masters and higher national diploma degree, this trend cut across the QCO, PS and ICTOs. The ICTOs has predominantly masters and bachelor degrees beside other certifications that are not classified in this category. Most of the production managers and supervisors has adequate practical background which enables them to be suitable for the purpose of the research.

Respondent cadre	Frequency	Percentage (%)
Production Supervisor	23	31.50
Production Manager	20	27.40
Quality Control Officer	20	27.40
ICT Officer	10	13.70
Total	73	100

Table 1.
Respondents Category.

Year experience	PM	QCO	PS	ICTO
BSc.[Bachelor]	—	5	5	3
MSc.[Masters]	5	5	10	7
HND[Diploma]	5	5	4	—
Trade Certificates	10	5	4	—
Total	20	20	23	10

Legend: Production Manager-PM; Quality Control Officer-QCO, Production Supervisor-PS; ICT Officer-Information Communication Technology Officer.

Table 2.
Respondents Qualification Manufacturing Experience.

4.3 Adaptable areas of disruptions in the quality assurance monitoring and calibration in production process

In **Table 3**, adaptable areas of disruptions in quality assurance monitoring was presented highlighting the responses of respondents. There are a lot of areas in intelligent manufacturing that disruptions has taken place. Some of the areas includes system design, implementation and monitoring. Areas covered in the study, 10 areas of disruptions was identified they include; process design, analytical technology, platform technology, operation technology, intelligent spindle system, sensor based control units, intelligent system powered psychometric system, 3d

Adaptable areas in intelligent manufacturing	RAI	Rank
Process Design	0.869	1st
Sensor based control units	0.786	2nd
Platform technology	0.771	3rd
Analytical technology	0.754	4th
Operation technology	0.732	5th
Intelligent Sequencing System	0.679	6th
Intelligent system powered psychometric system	0.657	7th
Intelligent spindle system	0.631	8th
3D Design System	0.579	9th

Legend: RAI—Relative Agreement Index.

Table 3.
Adaptable Areas of Disruptions in Quality Assurance Monitoring for Intelligent Manufacturing.

design system and intelligent sequencing system. This Process design is ranked 1st with RAI of 0.869; analytical technology is ranked 2nd with RAI value 0.786, platform technology with RAI 0.771 is ranked 3rd, operation technology is ranked 4th with RAI value of 0.754, intelligent spindle system also ranked 5th with RAI 0.732, sensor based control units ranked 6th, while intelligent system powered psychometric system and 3D design system and intelligent sequencing system were ranked 8th and 9th respectively with RAI values 0.631 and 0.579. In disruption that relates to intelligent manufacturing, there is always benefits often associated with paradigm shift in innovation technology. [36] opined that there are a lot of opportunities accrued to disruption that are beneficial although there is always negative resistance usually connected with a new change. There are risks associated with disruptions on account of new innovations often involved with the change.

However, any visionary organization should learn how to strategize in situation of associated risks mitigation. Intelligent manufacturing disruption has impacted strategic aspect of intelligent manufacturing that is changing the trend of games in product manufacturing. For instance, the following areas of intelligent manufacturing has been duly impacted; economy of product, economy of value chain, demand for product and changing faces of product as supported in [36, 37]. The associated risk in the disruption in intelligent manufacturing was modelled by [37–39] for monitoring of systemic sequencing of operation in product manufacturing. Disruption risk and pattern was modelled in [37] with Poisson ump process using random multiple system. Similarly parameters were sequenced and stochastically correlated to monitor quality diffusion process. However, internet of things (IoT), cyber-physical system, logistic 4.0, manufacturing 4.0, and hospital 4.0 are some of the aspect of disruption in intelligent manufacturing that formed the embodiment of application that has enhanced product production and manufacturing.

4.4 Drivers of effective quality control system monitoring in intelligent manufacturing

Drivers of effective quality control system culture adoption in intelligent manufacturing is presented in **Table 4**. From the data spread presented in the table, Effective monitoring of flow system with Relative Agreement Index (RAI) value of 0.873 is ranked 1st among other factors rated, Updated fault diagnostics and

Monitoring quality control parameters	RAI	Rank
Effective monitoring of flow system	0.873	1st
Updated fault diagnostics and rectification system	0.771	2nd
Effective design and production calibration system	0.769	3rd
Effective data extraction and transfer	0.754	5th
Intelligent cost control system	0.754	4th
Updated feedback control mechanism	0.732	6th
Adequate man-power planning	0.653	7th
Adequate machine part management	0.623	8th
Half live of machine parts	0.541	9th

RAI—Relative Agreement Index.

Table 4.
Drivers of Effective Quality Control System Culture Adoption in Intelligent Manufacturing.

rectification system RAI 0.771 is ranked 2nd, Effective design and production calibration system with RAI 0.769 ranked 3rd, Intelligent cost control system with RAI 0.754 ranked 4th, while Effective data extraction and transfer with RAI value of 0.754 is ranked 5th. However, Adequate machine part management with RAI 0.623 and Half live of machine parts with RAI value of 0.541 were ranked least with 8th and 9th position respectively.

Developing quality control is one of the important phase of manufacturing process. Quality control of product is very significant to the users and manufacturers. Quality to the manufacturer borders about correct design, authentic system calibration. Quality to consumer refers to manufactured product meeting users demand and expectation, therefore subjective in nature. ENQA (2009)in an adaptive study on standard and guidelines for quality assurance posited that there should be common reference point for quality assurance, keeping of quality register, procedure for quality assurance, keeping of quality register, documentation of procedure for the recognition of quality qualification and exchange of view among quality personnel. This could be encapsulated as a quality culture which should be keenly observed. Quality culture should be maintained so as to create a healthy production environment which guarantees customers production satisfaction. [40, 41] submitted further that quality culture would fine tune quality control value in a product system and this will lead to the reduction of political and geographical barrier). There are parameters that controls production in manufacturing industries, some of them includes: specification marketing, scheme and specification from purchasing units and agencies. Moreover, quality calibration at the outset of a manufacturing process usually ensures that quality product emerge from production system. Also, adoption of simple inspection table, and adoption of basic principles of sampling through sampling lot are cutting edge techniques that facilitates adoption of quality culture in product production, this toes the line of submissions in [20, 42].

4.5 Issues and challenges involved in adapting quality control systems in intelligent manufacturing

In this section challenges involved in the adapting of disruption application in intelligent manufacturing is outlined in **Table 5**. There are methods that could be used to control quality during manufacturing process [20, 21, 43] alluded that discrepancies in the document and. Process involved in manufacturing could be

Issues and challenges	PM	Rank	QCO	Rank	PS	Rank	ICTO	Rank
Machine–machine interaction	0.865	2nd	0.852	2nd	0.785	1st	0.773	1st
Man–machine interaction	0.873	1st	0.869	1st	0.721	2nd	0.653	2nd
Data quality	0.762	4th	0.754	4th	0.720	3rd	0.589	3rd
Cyber-security	0.771	3rd	0.771	3rd	0.698	4th	0.554	5th
Spare part management	0.762	4th	0.732	5th	0.657	5th	0.467	6th
Data Acquisition/Storage	0.657	5th	0.631	6th	0.589	6th	0.573	4th
Training Challenges	0.634	6th	0.543	7th	0.568	7th	0.457	7th
Testing cost & complexity	0.537	7th	0.557	7th	0.431	8th	0.456	8th

Legend: Production Manager-PM; Quality Control Officer-QCO, Production Supervisor-PS; ICT Officer-Information Communication Technology Officer.

Table 5.
Challenges involved in Adapting Quality Control System.

identified and process with different method, difficulty in the choice of correct method has been a challenge from time. In the context of this study, some significant challenges were profiled and processed. In relation to **Table 5**, some of the challenges profiled are stated as machine–machine interaction; man–machine interaction; data quality; cyber-security; spare part management; data acquisition/storage; training challenges and testing cost and complexity.

The respondents' opinion sample in this context about the challenges include that of production manager, quality control officer, production supervisors and ICT officers. The challenges are ranked in the appropriate order; machine–machine interaction, man–machine interaction, data quality, cyber-security, spare part management, data acquisition/storage, training challenges and testing cost & complexity. The production managers. ICT officers and Production supervisors ranked challenge of machine–machine interaction and man–machine interaction as 1st of the challenges; similarly, the same category of the managers ranked the same parameters 2nd according to the previous order. PS and ICO ranked data security and cyber security 3rd among other factors. Data quality was ranked 4th alongside Cyber security and data quality while data acquisition/storage; training challenges and testing cost and complexity were ranked 5th, 6th and 7th respectively by all categories of managers. Quality tools like Pareto diagram, Ishikawa diagram, Histogram, check-list, Flow chart and Control charts. However, statistical quality control method has been an age long method of quality control and this could be carried out with the aid of sample analysis, application of control charts and adoption of corrective measures.

4.6 Statistical test of level agreement of responses on issues and challenges involved in adapting quality control systems

Man Whitney U Test was carried out on the data in **Table 5** at significant level 0.05 two tailed, while the Test statistics results was presented in **Table 6**. The U-value is 24, the critical value of U at $P < 0.05$ is 8, therefore, the result is not significant at $P < 0.05$. Similarly, Z-score is 0.00. The P-value is 1.5 and 2.0, the result is not significant at 0.005. However, there is no significant difference in the opinion expressed by the respondents on the agreement level on Responses on issues and challenges involved in adapting quality control systems in intelligent manufacturing. It indicates high percentage of respondents in support of the fact that the KPI identified is in high order as presented on Likert scale 4 and 5 [23, 26].

From **Table 7** above, the Pearson Chi square results of the variables on Issues and Challenges Involved in Adapting Quality Control Systems is presented. From the table, the Pearson Chi-square row indicated that Chi value is 0.261, while P value is 0.05. This indicates that there is no statistical significance difference in association of respondents' opinion in the ranking of the issues and challenges involved in adopting control systems in intelligent manufacturing. The Null hypothesis is therefore accepted. It indicated that the factors were unanimously agreed upon. The implication lies in the fact that the listed factors in the tables were agreed upon by the respondents as critical challenge that poses threat and challenges to the intelligent manufacturing.

4.7 ANOVA of satisfaction level of facility managers on intelligent building systems' performance

Pearson's T and Student T test was carried out on mean of responses collated from the post occupation managers of the intelligent building used for the study and results presented in **Table 8**. The test was carried out to compare the difference in

Officers/managers	Production manager		Quality control officer		Production supervisor		ICT officer		Std. deviation	Std. error
Statistic items	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**	**—**	**—**
Machine–Machine interaction	1	1.500	1	1.500	1	1.500	1	1.500	—	—
	2	1.500	2	1.500	2	1.500	2	1.500	—	—
Man/machine Tradition	1	1.500	1	1.500	1	1.500	1	1.500	—	—
	2	1.500	2	1.500	2	1.500	2	1.500	—	—
Data Quality	1	1.500	1	1.500	1	1.500	1	1.500	—	—
	2	1.500	2	1.500	2	1.500	2	1.500	—	—
Cyber Security	1	1.500	1	1.500	1	1.500	1	1.500	—	—
	2	1.500	2	1.500	2	1.500	2	1.500	—	—
Spare parts Management	1	2.000	1	2.000	1	2.000	1	2.000	—	—
	2	1.000	2	1.000	2	1.000	2	1.000	—	—
Data Acquisition	1	2.000	1	2.000	1	2.000	1	2.000	—	—
	2	1.000	2	1.000	2	1.000	2	1.000	—	—
Training Challenges	1	2.000	1	2.000	1	2.000	1	2.000	—	—
	2	1.000	2	1.000	2	1.000	2	1.000	—	—
Testing and Complexity	1	1.500	1	1.500	1	1.500	1	1.500	—	—
	2	1.5000	2	1.5000	2	1.5000	2	1.5000	—	—

Table 6.
Man-Whitney U Student T-Test on Responses on Issues and Challenges Involved in Adapting Quality Control Systems.

Officers/managers	Production manager		Quality control office		Production supervisor		ICT officer	
Statistic items	**PS**	**KDT**	**PS**	**KDT**	**PS**	**KDT**	**PS**	**KDT**
Machine–Machine interaction	0.261	0.000	0.261	0.000	0.261	0.000	0.261	0.000
Man/machine Tradition	0.261	0.000	0.261	0.000	0.261	0.000	0.261	0.000
Data Quality	0.261	0.000	0.261	0.000	0.261	0.000	0.261	0.000
Cyber Security	0.238	0.030	0.238	0.030	0.238	0.000	0.238	0.000
Spare parts Management	0.238	0.164	0.238	0.164	0.238	0.091	0.238	0.091
Data Acquisition	0.261	0.000	0.261	0.000	0.261	0.000	0.261	0.000
Training Challenges	0.261	0.391	0.261	0.391	0.261	0.261	0.261	0.204
Testing and Complexity	0.261	0.000	0.261	0.000	0.261	0.261	0.261	0.000

Ho: There is no statistical difference in the managers' opinion as regards the Issues and Challenges Involved in Adapting Quality Control Systems.

Table 7.
Chi-Square Test on Issues and Challenges Involved in Adapting Quality Control Systems.

means of the post occupation facility managers and users. This is to check whether there variation among the group observed. The test results of equality of variance is as presented in the table. The test was performed at 95% confidence interval and all variables presented exhibited P-value higher than 0.05 i.e. $P > 0.05$. The result

ANOVA						
		Sum of squares	df	Mean square	F	Sig.
Machine to machine	Between Groups	1.000	3	.333		
	Within Groups	.000	0			
	Total	1.000	3			
Man to machine	Between Groups	1.000	3	.333		
	Within Groups	.000	0			
	Total	1.000	3			
Data quality	Between Groups	1.000	3	.333		
	Within Groups	.000	0			
	Total	1.000	3			
Cybersecurity	Between Groups	2.750	3	.917		
	Within Groups	.000	0			
	Total	2.750	3			
Spare parts	Between Groups	2.000	3	.667		
	Within Groups	.000	0			
	Total	2.000	3			
Data acquisition	Between Groups	2.750	3	.917		
	Within Groups	.000	0			
	Total	2.750	3			
Training challenges	Between Groups	.750	3	.250		
	Within Groups	.000	0			
	Total	.750	3			
Testing cost complexity	Between Groups	1.000	3	.333		
	Within Groups	.000	0			
	Total	1.000	3			

Table 8.
ANOVA of Satisfaction Level of Facility Managers on Intelligent Building Systems' Performance.

statistics implies that there is no significant difference in the means value the samples of the managers, therefore, the Null hypothesis is accepted, implying that there is no variation in the mean values of satisfaction level of production managers of the sampled companies. The reasons behind the difference could be linked to the background experience of the manager in intelligent manufacturing process.

Critical factors influencing intelligent manufacturing adaptation is presented in **Table 9**. The factors were broadly divided into four main categories, the technical related factors, political related factors, economic related factors and digital divide related factors. Main factors that are rated high belong to the technological related factors and were ranked 1st 2nd, 3rd and 4th, for instance, some production managers, quality control officers, production supervisor and ICT officers ranked category of factors that are technological related high, such as cost of talent, cost of technological failure, technological exchange problem and complexity in testing cost. Similarly, political related factors such as political will, technological content regulation and infrastructural environment provision are ranked 4th, 5th and 6th while digital divide factors were ranked 7th, 8th, 9th and 10th.

Critical factors parameters	PM	Rank	QCO	Rank	PS	Rank	ICTO	Rank
Technological Related Factor								
Cost of talent	0.885	1st	0.863	1st	0.785	1st	0.783	2nd
Cost of failure	0.883	2nd	0.861	2nd	0.721	5th	0.853	1st
Technological exchange	0.771	4th	0.757	5th	0.720	6th	0.759	4th
Testing cost and complexity	0.776	3rd	0.751	6th	0.698	7th	0.654	6th
Political Related Factor								
Government policy	0.766	7th	0.762	4th	0.657	9th	0.766	3rd
Technological content regulation	0.653	8th	0.651	7th	0.589	10th	0.651	7th
Provision of infrastructure environment	0.647	13th	0.643	8th	0.568	11th	0.457	14th
Political will for approval	0.653	8th	0.765	3rd	0.765	3rd	0.743	5th
Economic Related Factors								
Interplay of micro-economic variables	0.557	11th	0.587	9th	0.431	13th	0.456	14th
Interplay of macro-economic policy	0.766	7th	0.534	10th	0.678	8th	0.532	12th
Inter-continental technology transfer	0.765	5th	0.447	13th	0.787	2nd	0.521	13th
Digital divide related factors								
Data acquisition and storage	0.567	10th	0.531	12th	0.532	12th	0.654	8th
High regulation requirement	0.553	11th	0.534	10th	0.765	3rd	0.654	9th
Large state space	0.463	12th	0.503	11th	0.763	4th	0.503	11th

Legend: Production Manager-PM; Quality Control Officer-QCO, Production Supervisor-PS; ICT Officer-Information Communication Technology Officer.

Table 9.
Critical Factors Influencing Intelligent Manufacturing Adaptation.

Intelligent manufacturing is multidisciplinary in nature. This indicate that there are several intervening factors that influences success of intelligent manufacturing. Some of the significant factors are industrial chain factor, development factor, capital availability factor, political factor and socio-economic factors [44]. Submitted that chain factor, developing factor and capital factors influences the effectiveness of intelligent manufacturing system, the factors according to the study was described as engine to the effectiveness of intelligent manufacturing concept. Chain value system in supplying of materials for manufacturing is somehow significant, it borders about micro and macro supply chain system, and this toes the line of submissions in [45–47]. Similarly, there are issues that surrounds effective transition into intelligent manufacturing from traditional manufacturing system. While traditional manufacturing is transiting into intelligent manufacturing for the production of customized product involved principally. [46, 48] presented issues on important factors that should be taken into consideration in intelligent manufacturing.

The study revolves around actions to be taken to eliminate the challenges in manufacturing. Some of the actions include benchmarking capital factor, development factor and chain factor, the factors listed according to [48–51] formed the basis of the ideals in intelligent manufacturing and has tendency to transform traditional manufacturing production to customized product often associated with intelligent manufacturing. Moreover, [36] Adnan (2017) posited that manufacturing process and manufacturing organization responds to factors such as organization performance, organization culture, socio-economic reality and supply chain management. This fact is further corroborated in [52–55].

Officers/managers	Production manager		Quality control officer		Production supervisor		ICT officer		Std. deviation	Std. error
Statistic items	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**	—	—
Technological Related Factor Cost of talent	1	1.300	1	1.300	1	**1.300**	**1**	**1.300**	—	—
	2	1.300	2	1.300	2	**1.300**	**2**	**1.300**	—	—
Cost of failure Technological exchange	1	1.300	1	1.300	1	**1.300**	**1**	**1.300**	—	—
	2	1.300	2	1.300	2	**1.300**	**2**	**1.300**	—	—
Testing cost and complexity Political Related Factor	1	1.300	1	1.300	1	**1.300**	**1**	**1.300**	—	—
	2	1.300	2	1.300	2	**1.300**	**2**	**1.300**	—	—
Government policy Technological content regulation	1	1.300	1	1.300	1	**1.300**	**1**	**1.300**	—	—
	2	1.300	2	1.300	2	**1.300**	**2**	**1.300**	—	—
Provision of infrastructure environment Political will for approval	1	2.000	1	2.000	1	**2.000**	**1**	**2.000**	—	—
	2	1.000	2	1.000	2	**1.000**	**2**	**1.000**	—	—
Economic Related Factors Interplay of micro-economic variables	1	2.000	1	2.000	1	**2.000**	**1**	**2.000**	—	—
	2	1.000	2	1.000	2	**1.000**	**2**	**1.000**	—	—
Interplay of macro-economic policy Inter-continental technology transfer	1	2.000	1	2.000	1	**2.000**	**1**	**2.000**	—	—
	2	1.000	2	1.000	2	**1.000**	**2**	**1.000**	—	—
Digital divide related factors Data acquisition and storage	1	1.300	1	1.300	1	**1.300**	**1**	**1.300**	—	—
	2	1.300	2	1.000	2	**1.000**	**2**	**1.300**	—	—
High regulation requirement	1	1.300	1	1.300	1	**1.300**	**1**	**1.300**	—	—
	2	1.300	2	1.000	2	**1.000**	**2**	**1.300**	—	—
Large state space	1	2.000	1	1.300	1	**2.000**	**1**	**2.000**	—	—
	2	1.000	2	1.000	2	**1.000**	**2**	**1.000**	—	—

Table 10.
Man-Whitney U Student T- Test on Critical Factors Influencing Intelligent Manufacturing Adaptation.

Man Whitney U Test was carried out on the data in **Table 9** and presented in **Table 10**, at significant level 0.05 two tailed. The U-value is 24, the critical value of U at $P < 0.05$ is 8, therefore, the result is not significant at $P < 0.05$. Similarly, Z-score is 0.00. The P-value is 1.5, the result is not significant at 0.005. However, there is no significant difference in the opinion expressed by the respondents on the agreement level by production managers, production supervisors, quality control officers, and ICT officers. it indicates high percentage of respondents in support of the critical factors influencing intelligent manufacturing adaptation which supports the fact that the KPI identified is in high order as presented on semantic rating Likert scale 5 and 4 [21, 22, 56].

5. Conclusions

The study has censored and profiled the issues, facts, ideals and factors that influences the adoption of disruptions in creating adaptive intelligent manufacturing with a view to creating enhanced productivity in intelligent manufacturing.

Literature review was conducted background for the study and set stage for identification of missing links and gaps. The Intelligent manufacturing has been noted to be fairly new in the developing countries [11–13]. Ten (10) areas of disruptions was identified in this study, include; process design, analytical technology, platform technology, operation technology, intelligent spindle system, sensor based control units, intelligent system powered psychometric system, 3D design system and intelligent sequencing system.

In the context of this study, some significant challenges were profiled and processed. Some of the challenges profiled include machine–machine interaction; man–machine interaction; data quality; cyber-security; spare part management; data acquisition/storage; training challenges and testing cost and complexity. The validity of the outcome of this research lies in applicability in expanding frontiers of knowledge in literary research, assistance to policy makers, assistance to the production managers and personnel among others. The study finally presents areas of disruptions in the quality assurance monitoring and calibration in production process, issues and challenges involved in quality control systems in manufacturing, emerging areas of application and recommendation for improvement.

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Conflict of interest

The authors declare no conflict of interest in this research work. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Author details

Amusan Lekan[1,2]*, Clinton Aigbavboa[1], Moses Emetere[3] and James Owolabi[2]

1 Department of Construction Management and Quantity Surveying, Faculty of Engineering and Built Environment, University of Johannesburg, Doorfotein Campus Johannesburg, South Africa

2 Building Technology Department, College of Science and Technology, Covenant University, Ogun State, Nigeria

3 Department of Physics, College of Science and Technology, Covenant University, Ogun State, Nigeria

*Address all correspondence to: lekan.amusan@covenantuniversity.edu.ng

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